Position Tracking in Urban Environments using Linear Constraints and Bias Pseudo Measurements

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Abstract:

In many GPS-Sensor based tracking applications, the obtained measurements suffer from time a correlated bias. This is due to shadowing and multipath scattering of the wireless GPS signals. In this paper, we applicate a *Schmidt-Kalman Filter* (SKF) in order to improve the tracking process of ground vehicles on roads. We investigate possibilities to integrate bias measurements obtained from road information into the position tracking filter. To this end, we assume a digital map is given which contains road information for the observed region. The estimated position by the sensor data is projected onto the road as a hard constraint. This enables us to detect and to eliminate regular sensor bias by extending the estimate state of the target by an estimate of the sensor bias.

1 Introduction

Nowadays, there are a vast amount of tracking applications based on GPS sensors, as the sensors have become available for low cost and the GPS system is freely available everywhere around the world. However, the accuracy of a position depends on the number of satellites the sensor can receive. Moreover, shadowing and multipath scattering influence the position measurements significantly. In particular, in urban environments or in canyons, the shadowing effect leads to a time correlated *sensor bias* [9, 10].

In this paper, we focus on tracking ground moving target (such as vehicles or pedestrian in an urban area) using road information. The goal is to incorporate additional information in order to improve the track. Assuming perfect detection, linear dynamics and sensor model, and zero mean Gaussian error distributions, the Kalman filter is optimal in the mean squared error sense. In order to obtain a consistent filter, the dynamic model and properties of the sensors must be modeled appropriately. In our approach, we process *pseudo measurements* in order to estimate the current bias of the sensor. This work presents the structure and the parametrization for this virtual sensor.

Assume there is a target moving on roads of which we have digital road maps available. Then, it is possible to obtain a more accurate estimate by extending a Kalman filter as de-

scribed in the the following steps. (1) Filter the position measurement in the Kalman filter. (2) Search the next road segment best matching the current filtering output and project the position onto that segment. (3) Obtain a sensor bias measurement by calculating the line connecting the actual sensor position measurement and the projected position. (4) Let the Kalman filter process this bias measurement in order to estimate the current bias.
By doing so, shadowing effects on the wireless GPS signal are much better compensated by the Kalman filter for the next position data coming in.

2 State Estimation with Linear Constraints

In order to restrict the space where a target is possibly moving to roads, one can use linear constraints. Those are straight lines that represent segments of a road. There are a couple of possibilities to integrate linear constraints with the state estimation: (1) Use the constraints directly in the estimation process. The dynamic model is projected onto the constraints and then used as input for the Kalman filter. (2) Consider the linear constraints as pseudo measurement. (3) *Track-to-road fusion* (T2RF)- the measurement data is filtered without any constraints, then the output is constrained. T2RF is the methodology we use in this paper.

2.1 Road Approximation

Roads are usually not ideally straight lines. They need to be approximated before they can be used as linear constraints. A straight road segment can be directly represented in Hesse Normal Form as a point (r, θ) on the plane. Here, r represents the distance to point of origin, while θ stands for the angle to the x-axis. Roads with curves must first be divided into segments which are then represented as lines as well. Then, a curve consists of a series of straight segments that approximate it.

The road segment closest to the estimated state is relevant for the linear constraint construction. Let n be the normal vector of this segment, then

$$n = [\cos\theta, \sin\theta]^\top \tag{1}$$

Moreover, let $p = [x, y]^\top$ be the position of the target and v its speed on the line. v is perpendicular to n. Thus, the following statement holds according the definition of the dot product: $v^\top n = 0$, and $p^\top n = r$ due to $p^\top n = [x, y] \cdot \begin{bmatrix}\cos\theta \\ \sin\theta\end{bmatrix} = x \cdot \cos\theta + y \cdot \sin\theta$. Combining those conditions with the line equation in hough space results in: $D\mathrm{x}_k = d$ where $D = \begin{bmatrix}\cos\theta & \sin\theta & 0 & 0 \\ 0 & 0 & \cos\theta & \sin\theta\end{bmatrix}$, and $d = \begin{bmatrix} r \\ 0 \end{bmatrix}$. The state of the object is given by $\mathrm{x}_k = [x, y, \dot{x}, \dot{y}]^\top$. Both variables may be time dependent.

2.2 Projection on a Road

As previously mentioned, the projection of a state on the road is an optimization problem with constraints. The constraints from previous subsection can now be used on the output of the Kalman filter. The road equation is interpreted as a surface $\mathcal{S} = \{\mathrm{x} : D\mathrm{x} = d\}$, containing possible positions of the target, on which the state estimate $\hat{\mathrm{x}}$ will be projected. The proper point can be calculated in different ways depending on the definition of the proximity. Simple metrics such as the euclidean distance may be used. It is also possible to take more information into account, e.g. direction and speed of the target's movement. In the second case a symmetric positive-definite weighting matrix W would be used to define the proximity. The optimization problem is now as follows:

$$\breve{\mathrm{x}} = \mathrm{argmin}_{\mathrm{x} \in \mathcal{S}} (\mathrm{x} - \hat{\mathrm{x}})^\top W (\mathrm{x} - \hat{\mathrm{x}}) \tag{2}$$

The squared euclidean distance $(\mathrm{x} - \hat{\mathrm{x}})(\mathrm{x} - \hat{\mathrm{x}})$ is weighted with matrix W. If $W = I$ only the euclidean distance will be considered. The use of the covariance matrix P of the estimation error for weighting is highly recommended. If $W = P^{-1}$ then the covariance of the constrained result is smaller than the covariance of the unconstrained one.

The optimization equation above is easily solvable with a method called Lagrange multiplier. First, the Lagrange function is constructed:

$$\Lambda(\mathrm{x}, \lambda) = (\mathrm{x} - \hat{\mathrm{x}})^\top W (\mathrm{x} - \hat{\mathrm{x}}) + 2\lambda^\top (D\mathrm{x} - d) \tag{3}$$

Solving gradient equation $\nabla_{\mathrm{x},\lambda} \Lambda(\mathrm{x}, \lambda) = 0$ results in:

$$W(\mathrm{x} - \hat{\mathrm{x}}) + D^\top \lambda = 0 \tag{4}$$

$$D\mathrm{x} - d = 0 \tag{5}$$

After some calculations the resulting state projected on the constraints is as follows:

$$\breve{\mathrm{x}} = \hat{\mathrm{x}} - W^{-1} D^\top (D W^{-1} D^\top)^{-1} (D\hat{\mathrm{x}} - d) \tag{6}$$

3 Filtering with Bias

Filtering with linear constraints provides an improvement of the state estimation if the target moves on roads. The output is a trace constrained by roads that are approximated as lines. However, the accuracy of the road projection depends to a great extent on the output of the measurement filtering in the Kalman filter. This step has a potential of improvement. In many applications, sensors are subject to time correlated bias. To overcome this challenge, one might use the Schmidt Kalman filter [1], which incorporates bias into the Kalman filter.

3.1 Bias Processing

When the filtering of a sensor measurement has been finished, the output can be projected on the road, as described in the previous chapter. The bias can be interpreted as the difference between measurement and the result of the projection. Nevertheless, the bias calculated in such a way suffers the same effects of inaccuracy as the sensor measurement. Therefore, after the bias has been *measured*, it will be filtered in a similar way to the one above. To do this, some changes in the filter have to be made.

Let $\breve{\mathrm{x}}_k^b$ be the output $\hat{\mathrm{x}}_k^b$ of the filter projected onto the approximated road according to section 2.2. Then the bias measurement is defined as follows:

$$\mathrm{z}_k^b = \mathrm{z}_k - \hat{\mathrm{x}}_k^b \tag{7}$$

with z_k being the current sensor position measurement. As only the bias from the target's state is needed, the measurement matrix must be modified:

$$H_k^b = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}. \tag{8}$$

Then, the measurement error covariance is changed to the value γ_b that is appropriate for the bias:

$$R_k^b = \begin{bmatrix} \gamma_b & 0 \\ 0 & \gamma_b \end{bmatrix}. \tag{9}$$

Moreover, with each road projection, the covariance of the filtering estimate changes by the squared distance between the current and the last output. This should be taken into consideration:

$$\breve{P}_k^b = \hat{P}_k^b + \Delta\mathrm{x}\Delta\mathrm{x}^\top, \tag{10}$$

with $\Delta\mathrm{x} = \breve{\mathrm{x}}_k^b - \hat{\mathrm{x}}_k^b$. Now, the bias filtering can be carried out with the modified values. To this end, the bias is interpreted as a measurement. The result is a new bias extended state that is more appropriate, as several additional aspects, e.g. target's speed and direction, is taken into account. After that, the changed values, such as measurement matrix and measurement error covariance, should be set back to ensure proper sensor measurement prediction and filtering in the next time step.

4 Evaluation

In this section, exemplary evaluation results of an implementation of the Kalman filtering with bias and linear constraints are presented. The input is a series of time stamped positions of the target measured with a standard GPS tracker. As background information, the

(a)

(b)

Figure 1: (a) Output of the Kalman filter with linear road constraints. The red line is the output of the Kalman filter, the green line shows the result of projecting this output on roads. Where no projection is needed the result of the Kalman filter is taken as is. (b) Result of the Kalman filter with bias and linear road constraints. The green line represents the final output, the red parts are present at places where filtering output with bias does not match the final output.

roads were not given as a set of curves or straight lines. But detailed data on buildings was available. Thus, the roads were approximated from the surrounding buildings' walls. The traced target moves in walking speed and strictly outside of the buildings. Nevertheless, the noise and other factors cause the trace points being placed at least half of the time inside the buildings. It appears as if the target would move through walls.

Our goal was to eliminate this effect. Thus, we applied the Kalman filter with linear constraints on the trace. The result is shown in Fig. 1 (a). The Kalman Filter only smoothes the trace completely ignoring the building data. Then, each trace point is projected onto next road without any feedback for the filter. This leads to straight, unnatural looking trace segments on roads where the projection was used (which was the case most of the time). A total of 334 points had to be projected. It is possible to reduce the frequency of the projection, if the filtering output is more appropriate and if the bias is taken into account. Fig. 1 (b) shows the results of the method described in this paper. The Kalman filter with bias and linear road constraints.

The trace looks now much more natural and there are only a few places (marked red) where the output of the Kalman filter does not match the final projected output of the whole algorithm. These are e.g. places where a filtered trace point lies inside a building. In total there were 46 projections needed which is a significant improvement to the 334 in the case where no bias has been used.

5 Conclusion

In this paper, we presented an improved position tracking scheme for urban environments using road map information. Due to shadowing and scattering, such circumstances often lead to time correlated measurement bias when GPS sensors are utilized. Therefore, it is a great benefit to use a Schmidt-Kalman filter which estimates the sensor bias beneath the target's state. Moreover, background information such as road maps might be included into the filtering process. This yields a reliable estimate for the current sensor bias. Combining both approaches leads to a significant reduction of the amount of states that have to be projected onto the road. This was confirmed by an evaluation using a pedestrian trace of a GPS sensor and a city map picture. In the future, we plan to explore other techniques for the linear constraint filtering and their extension to the bias extended Schmidt-Kalman filter.

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